

The effect of COVID-19 on the global stock market

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Abstract

This paper investigates the effect of COVID-19 on the global stock market. Specifically, we test whether the growth in the number of confirmed cases/deaths affects market quality, measured by return, realised volatility, jumps and co-jumps for 43 stock indices around the world. We find that an increase in the growth rate of the number of confirmed cases increases volatility and jumps while reducing return. Further, we explore whether economic, financial and political risks play any significant role in the relation between the number of confirmed cases/deaths and market quality. Overall, we find the risk from COVID-19 overshadows these risks.

Key words: Country risks; COVID-19; Stock markets; Volatility

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1. Introduction

In just a matter of weeks, the contagious virus COVID-19 spread around the world, leading to a global pandemic and destructive economic impacts on an

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unparalleled scale (see Baldwin and Di Mauro, 2020; Goodell, 2020). Despite extensive research related to COVID-19, our understanding of COVID-19 and its effects on market quality are still relatively limited. The outbreak of COVID-19 caused more frequent stock market index jumps than any other period in history with the same number of trading days (Baker *et al.*, 2020). Yet, there is minimal scrutiny of the impact of the pandemic on jumps and co-jumps of stock indices. This paper fills this gap in the existing literature by investigating how COVID-19 affects returns, volatility, and jumps of the stock market indices. Further, it explores whether COVID-19 causes global stock market indices to jump with the S&P500 index. Finally, it assesses whether country risk improves or impairs the above relationships.

This new infectious disease is distinct from and much more dangerous than previous outbreaks (Alfaro *et al.*, 2020; Baker *et al.*, 2020; Jackwerth, 2020). Not only does it lower market returns, it also increases the volatility of the stock market (Al-Awadhi *et al.*, 2020; Ashraf, 2020; Erdem, 2020; Ramelli and Wagner, 2020). Nevertheless, the impact of COVID-19 has caused investors to suffer significant losses in a short period of time due to a very high level of risks (Zhang *et al.*, 2020). Although the COVID-19 shock has been global, not all countries have been impacted in the same way, and they have not reacted in the same way. Some researchers identify firm characteristics which soften the adverse effects of the health crisis (Albuquerque *et al.*, 2020; Fahlenbrach *et al.*, 2020; Ramelli and Wagner, 2020), while others suggest political and social progress are key determinants in explaining the heterogeneous impacts of COVID-19 on stock returns across countries (Greer *et al.*, 2020).

Stock volatility is not directly observable, but rather inherently latent. In response, several studies, such as Andersen *et al.* (2010), Andersen *et al.* (2011) and Phiromswad *et al.* (2021), advocate the use of so-called realised volatilities (constructed from the summation of the squared intraday interval return) as a practical method for improving the ex-post volatility measures. Theoretically, these realised volatilities are free from measurement error (Andersen *et al.*, 2003). In addition, Andersen *et al.* (2003) indicate that simple models of realised volatility outperform the well-known GARCH and related stochastic volatility models in out-of-sample forecasting. In our analysis, we separate the realised volatility into continuous and discontinuous jump components by using the nonparametric techniques developed by Barndorff-Nielsen and Shephard (2004). These components correspond to the expected and unexpected new events. Prior research indicates that financial market jumps are responsible for the majority of market volatility, especially during crisis periods (Chan *et al.*, 2014).

We contribute to the literature in several respects. First, we add to the literature that utilises high-frequency data to capture volatility dynamics (e.g., Andersen *et al.*, 2003; Tanthanongsakkun *et al.*, 2018; Ho *et al.*, 2021; Phiromswad *et al.*, 2021). For instance, Phiromswad *et al.* (2021) examine co-jumps of 54 cryptocurrencies with the Thai stock market. Wang *et al.* (2020)

investigate the usefulness of the implied volatility index (VIX) and the economic policy uncertainty (EPU) index in forecasting future volatility for 19 equity indices, finding that the VIX is a better predictor than the EPU index during the coronavirus pandemic. Chan *et al.* (2014) examine whether currency jumps are more severe in emerging markets, especially during crises, while Dungey *et al.* (2014) use high frequency data to detect stress dates in currency markets. Our analysis complements the financial market studies of Wang *et al.* (2020), Chan *et al.* (2014) and Dungey *et al.* (2014), who examine the impact of crises on volatility dynamics. More specifically, by decomposing volatility into continuous and discontinuous jump components, this paper provides a novel way to understand the impact of COVID-19 on the volatility of stock indices. This method is also less vulnerable to market microstructure noise, which is a key concern in the asset pricing literature (Andersen *et al.*, 2007).

Our findings also relate to the impact of the pandemic on the co-movements of global markets (e.g., Akhtaruzzaman *et al.*, 2020; He *et al.*, 2020; Okorie and Lin, 2020). Akhtaruzzaman *et al.* (2020) report a significant increase in stock market correlations between China and G7 countries during the pandemic period. Similarly, He *et al.* (2020) document that the impact of COVID-19 on the European and US stock markets has a backflow effect on the Asian stock markets, particularly China. Distinct from these studies, we exploit the intraday 5-min return to construct co-jumps of the US stock index and other stock market indices around the world.

As such, our paper is part of the emerging literature which examines the impact of COVID-19 on financial outcomes (e.g., Al-Awadhi *et al.*, 2020; Ashraf, 2020; Erdem, 2020; Ramelli and Wagner, 2020). Alfaro *et al.* (2020) examine the relationship between unanticipated changes in COVID-19 infections and aggregate market returns. Baker *et al.* (2020) and Zaremba *et al.* (2020) investigate the effect of government interventions in contributing to stock market volatility. Building on this literature, our study provides novel evidence of the heterogeneous impacts of COVID-19 on stock returns across countries.

Based on 43 5-min intraday stock indices over the period 30 October 2019–13 May 2020, our results suggest that the COVID-19 pandemic has exerted a negative and significant impact on market quality across the globe. In particular, we show that the pandemic negatively affects stock market returns but positively affects stock market volatility, jumps and co-jumps. Furthermore, there is weak evidence suggesting that country risk lowers the impact of COVID-19 on market quality.

The remainder of this paper is organised as follows. Section 2 reviews related literature and develops hypotheses. Section 3 describes the data and methodology. Section 4 presents empirical results and Section 5 concludes.

2. Literature review and hypothesis development

The efficient market hypothesis (EMH) assumes that all investors are rational and stock prices adequately reflect all available information. However, many financial anomalies (such as excess volatility and systemic under- or over-valuation of stock prices relative to their intrinsic values) cannot be explained by the EMH. Behavioural finance researchers believe investor sentiment may help to explain these market anomalies. According to Black (1986) and De Long *et al.* (1990), there are two types of investors: informed rational investors and noise traders. Rational informed investors, who are sentiment free, form rational expectations about the expected future cash flow of asset values. In contrast, uninformed noise traders experience waves of irrational sentiment and tend to form cognitive bias expectations, causing strong and persistent mispricing. Both types of investors compete in the market and set prices and expected returns; hence, the equilibrium price reflects the opinions of both rational investors and noise traders.

External and unexpected shocks, such as a financial crisis or disease outbreak, can affect economic trends and suddenly change investors' sentiments. When the market is trending downward, investors behave more pessimistically, leading to upward revisions in volatility and lower future excess returns (Lee *et al.*, 2002). Burns *et al.* (2012) suggest that perceived risk and negative emotions often escalate in the initial stage of a crisis as the public responds to news reports, social media and social interaction with friends and family. Along the same line, Roszkowski and Davey (2010) document the dramatic increase in the public's perception of the risk inherent in investing during the financial crisis of 2008.

The impact of investor sentiment on the stock market during a crisis is well documented. Several empirical studies rely on VIX as a proxy for the overall attitude or tone of investors towards future cash flows and investment risk of a particular security or financial market (see, e.g., Altig *et al.*, 2020; Cheng, 2020; Jackwerth, 2020). A rising VIX implies an increased need for protection against risk and is a sign of increasing market volatility; in particular, VIX is used as a measurement of investors' fear. Other researchers focus on implied volatility from stochastic volatility models (see, e.g., Alan *et al.*, 2020; Mirza *et al.*, 2020). Nevertheless, in practice, stock volatility is not directly observable. Andersen *et al.* (2001) and others suggest the use of so-called realised volatilities, constructed from the summation of the squared intraday interval return, as a practical method for improving the ex-post volatility measures. It is free from measurement error and outperforms the well-known GARCH and related stochastic volatility models in out-of-sample forecasting (Andersen *et al.*, 2003).

COVID-19 is much more than a health crisis; it is also very much an economic crisis that has affected the lives of many individuals, families and businesses across various industries globally. The global financial markets

reacted very strongly and stock market returns dropped sharply as the COVID-19 pandemic grew (Al-Awadhi *et al.*, 2020; Ashraf, 2020; Erdem, 2020; Ramelli and Wagner, 2020). However, the impact of the increasing number of deaths on the stock market remains unclear.¹

As more and more cases were diagnosed, investors became wary about the unusual uncertainty surrounding the financial markets, leading to a highly volatile and unpredictable market situation. Baker *et al.* (2020) note that from 24 February to 24 March 2020, there were 18 market jumps, largely due to reactions to news about COVID-19 in the United States. Alfaro *et al.* (2020) show that US stock returns respond to daily unanticipated changes in COVID-19 infections, implying declining stock market volatility as the pandemic became less uncertain. Alan *et al.* (2020) and Zaremba *et al.* (2020) demonstrate the impact of governments' policy response to the pandemic on stock market volatility. Similarly, Zaremba *et al.* (2021a) investigate the role of non-pharmaceutical interventions in equity market liquidity. Finally, Zhang *et al.* (2020) find that the number of COVID-19 confirmed cases causes an increase in country-specific risks in stock markets as well as systemic risks.

Globalisation has linked global economies and increased the interdependence of global financial markets. Akhtaruzzaman *et al.* (2020) show that listed firms across China and G7 countries have experienced significant increases in the conditional correlations regarding market returns during the pandemic. This finding is supported by Okorie and Lin (2020), who suggest a fractal contagion effect of COVID-19 on the stock market. They also highlight that this fractal contagion effect vanishes in the middle and long run for both stock market return and volatility. Likewise, He *et al.* (2020) argue that the impact of COVID-19 on stock markets has bidirectional spillover effects between Asian countries and European and American countries. Nevertheless, there is no evidence to suggest that COVID-19 has a negative impact on these countries' stock markets greater than the global average, as measured by the S&P Global 1200 index. In contrast, Tokic (2020) suggests that COVID-19 will accelerate the trend of de-globalisation and de-dollarisation. Consistent with this finding, Zhang *et al.* (2020) suggest that countries respond differently to national-level policies and the general development of the pandemic; specifically, they show that the US stock market has failed to take a leading role in this regard.

In view of the above discussion, the COVID-19 outbreak has resulted in exaggerated fear, uncertainty and pressure on stock markets. Consistent with the EMH, market participants incorporate news about COVID-19, especially the number of confirmed cases/deaths, into their valuation (Al-Awadhi *et al.*,

¹For instance, Ashraf (2020) suggests that stock markets react strongly with negative returns to growth in confirmed cases; however, response to the growth in deaths is not statistically significant. Al-Awadhi *et al.* (2020) and Erdem (2020) indicate that both the daily growth in total confirmed cases and in total deaths caused by COVID-19 have significant negative effects on stock returns.

2020; Ashraf, 2020; Erdem, 2020; Ramelli and Wagner, 2020). Nevertheless, the stock market seems to overreact to such news, resulting in stock market jumps and higher volatilities in the short run (Ashraf, 2020; Baker *et al.*, 2020; Okorie and Lin, 2020). There is some evidence to suggest that the spillover effect of COVID-19 impacts global economies (Akhtaruzzaman *et al.*, 2020; He *et al.*, 2020; Okorie and Lin, 2020). Thus, we hypothesise:

H1: If COVID-19 induces uncertainty in the stock market, then the increase in the number of COVID-19 confirmed cases/deaths should increase volatility, jumps and co-jumps while reducing stock returns.

The EMH suggests that competition among knowledgeable participants leads to a situation where stock prices incorporate all publicly available information. Consistent with this notion, research at the firm level suggests that the stock market reacts mostly to firms' pre-existing conditions that affect their ability to endure the crisis. Firms with less leverage (Ramelli and Wagner, 2020), more cash holdings (Alfaro *et al.*, 2020; Ding *et al.*, 2020) and greater financial flexibility (De Vito and Gómez, 2020; Fahlenbrach *et al.*, 2020) experienced less negative stock returns during the COVID-19 pandemic. Similarly, firms with better corporate social performance, as measured by environmental and social (ES) ratings, could suffer a lower decline in performance during a pandemic (Albuquerque *et al.*, 2020).

Other researchers explore how aggregate stock market returns across the world are responding to the COVID-19 pandemic. For instance, Liu *et al.* (2020) examine the short-term impact of the coronavirus outbreak on 21 leading stock market indices using an event study approach, finding that the COVID-19 outbreak has adverse impacts on stock indices' abnormal returns. In addition, their panel fixed-effect regression results suggest that COVID-19 increases stock investors' fear and creates pessimistic sentiment regarding future returns. Gormsen and Koijen (2020) analyse investors' expectations about economic growth evolving across horizons in response to the pandemic and subsequent policy responses, revealing that the US fiscal stimulus (around 24 March 2020) boosted the stock market and long-term growth but did little to increase short-term growth expectations.

Previous studies also suggest that fiscal capacity shapes the degree to which countries can respond effectively to the pandemic and hence how stock markets respond. Countries whose fiscal response would be constrained by debt might be thought to be more vulnerable to a pandemic. In line with this notion, Ding *et al.* (2020) show that stock markets in richer economies, as measured by GDP per capita, have weathered the pandemic better than those in poorer economies. Gerding *et al.* (2020) also consider the relationship between corporate characteristics and stock price reactions. Using individual stock-level data from more than 100 countries, they find that stock market responses were less negative in countries with higher fiscal capacity (i.e., lower debt-to-GDP ratios). Greppmair *et al.* (2020) suggest that during the COVID-19 pandemic,

short sellers have been trading on a combination of a firm's liquidity and a government's fiscal capacity. In addition, they find short-selling activity to be focused on illiquid companies headquartered in countries with a low credit rating. However, some suggest that not all debt capacity variables impact the effectiveness of interventions and policies at curbing the pandemic. Zaremba *et al.* (2021b) show equity investors seem to factor only labour market conditions in the potential risks associated with the spread of the pandemic. They argue that unemployment has a negative impact on consumption, thus directly affecting the performance of the stock market. To reinvestigate the role of the debt capacity variable during the pandemic, we incorporate the debt capacity variables and control for unemployment. Economic risk denotes a country's ability to pay back its debts. A country with strong economic health should provide more reliable investment than a country with weaker finances. We thus propose the following:

H2: If a country with low economic risk² implies stronger fiscal capacity, then the country should experience less decline in stock indices and lower stock volatility and jumps during the pandemic.

Financial risk is also an important determinant of a country's fiscal capability. It is often defined as a country's ability to finance its trade debt obligations. Since a country's capability to generate foreign exchange directly affects the capacity to repay foreign debt, we expect that:

H3: If a country with low financial risk³ implies stronger fiscal capacity, then the country should experience less decline in stock indices and lower stock volatility and jumps during the pandemic.

Previous studies suggest that national-level political characteristics are important for crisis management and recovery (Bosancianu *et al.*, 2020; Greer *et al.*, 2020). In times of crisis the people turn to the state for leadership and unified action, and thus one may suppose that a country requires more political institutions with centralised power to take forceful action to control the spread of the pandemic (Zaremba *et al.*, 2021b). Consistent with this argument, Ding *et al.* (2020) find that a country with greater state power, relative to the power of individuals, experienced smaller stock price declines during the COVID-19

²We use the economic risk index from Political Risk Services' International Country Risk Guide (ICRG) by the PRS Group. It reflects a country's ability to finance its official, commercial and trade debt obligations by using five variables, namely GDP per head, real GDP growth, annual inflation rate, budget balance as a percentage of GDP, and current account as a percentage of GDP.

³We use the financial risk index from ICRG by the PRS Group. It reflects a country's ability to finance through inflows of foreign exchange by using five variables, namely foreign debt as a percentage of GDP, foreign debt service as a percentage of exports in goods and services, current account as a percentage of exports in goods and services, net liquidity as months of import cover, and exchange rate stability.

pandemic. In contrast, Capelle-Blancard and Desroziers (2020) show the country's legal origin appears to have had no influence on stock market responses in 74 countries from January to April 2020.

On the other hand, some may argue that legitimacy, credibility and the trust people have in government are necessary for the people to respond through collaborative engagement with public authorities to address crises (Bosancianu *et al.*, 2020; Greer *et al.*, 2020). Countries with greater press freedom can benefit from better information flow and public trust. This notion is in agreement with Painter and Qiu (2021) and Barrios and Hochberg (2020), who find that political beliefs determine the perception of risk associated with COVID-19 and health-related decisions. In a similar vein, using a panel regression analysis of 75 countries, Erdem (2020) shows that the adverse effects of COVID-19 on the stock market are lower in freer countries.⁴ Pástor and Veronesi (2013) examine the impact of political uncertainty on stock returns, identifying that political uncertainty causes serious panic in the stock market, especially when the economy is weak.

At the same time, the spread of the pandemic might reduce the political tensions in a country, as saving lives take precedence over threats posed by other groups. However, as time goes by, the pandemic may aggravate existing conflicts and trigger some forms of social disorder. This notion is consistent with that of Sharif *et al.* (2020), who document an unprecedented increase in geopolitical risk levels in the US driven by the COVID-19 outbreak.⁵

Overall, there is no clear pattern across countries regarding the relation between political characteristics and stock market responses. We hypothesise that a country with less political stability, i.e., high political risk, may potentially destabilise financial markets and exacerbate crises. Thus, we hypothesise:

H4: Countries with high political risk⁶ experience higher stock volatility and jumps, and lower returns during the COVID-19 pandemic.

Country risk is an important factor affecting the debt service capacity of borrowing countries. It often refers to the political, economic and financial

⁴Erdem (2020) uses the Human Freedom Index 2019 from Freedom House as a proxy for the level of a country's freedom. This index adds scores of 10 political rights indicators and 15 civil liberties indicators.

⁵Sharif *et al.* (2020) use the GPR index as a proxy for geopolitical risk. This index is constructed based on news related to geopolitical events. The number of words related to geopolitical risk are counted each day in each newspaper to calculate the daily GPR index.

⁶We use the political risk index from ICRG by the PRS Group. It reflects a country's political stability by using 12 variables, namely government stability, socio-economic conditions, investment profile, internal conflict, external conflict, corruption, military in politics, religious tension, law and order, ethnic tensions, democratic accountability, and bureaucracy quality.

risks that are unique to a specific country, and which might lead to unanticipated investment losses. In a broader sense, country risk is the degree to which political and economic unrest affect the securities of issuers doing business in a particular country. Prior research suggests that short sellers focus on less liquid companies headquartered in countries with a low credit rating (Greppmair *et al.*, 2020). Thus, we hypothesise:

H5: Countries with high country risk⁷ experience higher stock volatility and jumps, and lower returns during the COVID-19 pandemic.

Overall, it appears that stock markets integrated both new information about COVID-19 and pre-existing conditions that affected firms' ability to endure the crisis. Nevertheless, there is scant analysis of the impacts on the jumps of stock market returns. This paper attempts to provide the first empirical insights into the COVID-19 pandemic and its effects on jumps and co-jumps across countries.

3. Data and method

3.1. Data and variables

To construct our sample, we retrieve 5-min intraday stock indices during the period 30 October 2019 to 13 May 2020 from Datascope provided by the Refinitiv database. The daily COVID-19 data are from the European Centre for Disease Prevention and Control (ECDC). The ECDC reports the numbers of new COVID-19 cases and deaths daily. The variables *COVID* and *Death* are the daily growth rates in the cumulative COVID-19 confirmed cases and deaths, respectively.

Following the literature, such as Andersen *et al.* (2003), Chan *et al.* (2014), and Tanthanongsakkun *et al.* (2018), we utilise 5-min interval returns to minimise the measurement error resulting from a decrease in microstructure biases. The return of the stock index is defined as the following:

$$R(t) = \sum_{j=1}^M r_{t,j} \quad (1)$$

where $r_{t,j}$ denotes the j th 5-min return for a stock index during day t , M denotes the total number of 5-min return intervals during any trading day, and $R(t)$ defines the daily return on day t , derived from the 5-min stock index.

The frequency of stock market index jumps during COVID-19 could be considerably higher than other previous disease outbreaks (Baker *et al.*, 2020).

⁷The country risk index reflects the uncertainty associated with investing in a particular country. It comprises 22 variables, representing three major components of country risk, namely economic, financial and political.

To capture this unprecedented stock market reaction to COVID-19,⁸ we follow the analysis in Andersen *et al.* (2007) by decomposing the realised volatility into separate continuous and discontinuous (jump) components based on the bipower variation measures proposed by Barndorff-Nielsen and Shephard (2004, 2006) (see also Andersen *et al.*, 2010, 2011; Chan *et al.*, 2014; Tanthanongsakkun *et al.*, 2018).

The volatility over the active part of the trading day t is measured by the quadratic variation

$$QV(t) = \int_{t-1}^t \sigma^2(s) ds + \sum_{j=0}^{N_t} k_{t,j}^2. \quad (2)$$

The first integrated variance term represents the contribution from the continuous price path, where N_t gives the number of jumps over day t , and $\sum_{j=0}^{N_t} k_{t,j}^2$ accounts for the corresponding contribution to the variance from the within-day jumps. Hence, in the absence of jumps, the quadratic variation is simply the integrated volatility of the continuous sample path of the cumulative return process:

$$IV(t) = \int_{t-1}^t \sigma^2(s) ds. \quad (3)$$

The components of Equation (2) are not directly observable. Instead, following prior literature, such as Andersen and Bollerslev (1998) and Andersen *et al.* (2003), non-parametric daily realised volatility, $RV(t)$, is defined using high-frequency intra-daily square returns as:

$$RV(t) = \sum_{j=1}^M r_{t,j}^2. \quad (4)$$

As suggested by Andersen and Bollerslev (1998) and Andersen *et al.* (2003), the realised volatility converges uniformly in probability to the quadratic variation process as the sampling frequency goes to infinity. That is, the realised volatility estimator does not consistently estimate integrated volatility as the measure captures both the continuous and discontinuous components of

⁸Identifying a jump is simply a way to construct one of our dependent variables. The nonparametric jump technique dates back to 2002 and four approaches are popular in the existing literature. We choose the Barndorff-Nielsen and Shephard (2004, 2006) approach as it is one of the earliest approaches and has been successfully adopted by various authors from 2002 until recently in 2021 (see Andersen *et al.*, 2003; Tanthanongsakkun *et al.*, 2018; Ho *et al.*, 2021; Phiromswad *et al.*, 2021).

volatility. Thus, the biopower variation measures developed by Barndorff-Nielsen and Shephard (2004, 2006) are used to disentangle the two components of the quadratic variation process. In particular, they show that the bipower variation, $BV(t)$, converges to the integrated volatility, $IV(t)$, for $M \rightarrow \infty$:

$$BV(t) \rightarrow IV(t) = \int_{t-1}^t \sigma^2(s) ds. \quad (5)$$

Although the use of very high frequency financial price data could increase the precision of the biopower variation estimate, it can potentially be seriously contaminated by market microstructure noise. To diminish the effects of the local serial correlation induced by microstructure noise, Huang and Tauchen (2005) suggest using staggered observed returns in the biopower variation estimate:

$$BV(t) = \mu_1^{-2} \left(\frac{M}{M-2} \right) \sum_{j=3}^M |r_{t,j-2}| |r_{t,j}| \quad (6)$$

where $\mu_1 = \sqrt{\frac{2}{\pi}} \cong 0.79788$. The bipower variation measure defined above involves an additional stagger relative to the measure originally considered in Barndorff-Nielsen and Shephard (2004), which makes it robust to certain types of market microstructure noise.

Combining the results in the previous equations, the difference between the realised variation and the bipower variation consistently estimates the jump contribution of the quadratic variation process, that is:

$$J(t) \equiv RV(t) - BV(t) \rightarrow \sum_{j=0}^{N_t} k_{t,j}^2. \quad (7)$$

Following prior research, such as Huang and Tauchen (2005), Andersen *et al.* (2007) and Tanthanongsakkun *et al.* (2018), we consider small changes as measurement errors or part of the continuous sample path process and treat the large values of the changes as the significant jump component. To determine if a movement is a significant jump on day t , we compute the Z statistic as follows:

$$Z(t) = \frac{\frac{RV(t) - BV(t)}{RV(t)}}{\sqrt{\left(\left(\frac{\pi}{2} \right)^2 + \pi - 5 \right) \frac{1}{M} \max \left(1, \frac{TQ(t)}{BV(t)^2} \right)}}. \quad (8)$$

This follows an asymptotically standard normal distribution under the null hypothesis of no within-day jumps, where:

$$TQ(t) = M\mu_{4/3}^{-3} \left(\frac{M}{M-4} \right) \sum_{j=5}^M |r(t, j-4)|^{4/3} |r(t, j-2)|^{4/3} |r(t, j)|^{4/3} \quad (9)$$

$$\text{and } \mu_{4/3} = 2^{2/3} \Gamma\left(\frac{7}{6}\right) \Gamma\left(\frac{1}{2}\right).$$

Based on the significant jump detection test statistic, the realised measure of the jump contribution to the quadratic variation of the price process is then measured by:

$$J(t) = I(Z(t) > \Phi_\alpha)(RV(t) - BV(t)) \quad (10)$$

where $I(\bullet)$ denotes the indicator function and Φ_α refers to the inverse of the standard normal distribution with a critical value of α .

Accordingly, we define integrated variance, $CV(t)$, such that the non-parametric measures for the jump and continuous components add up to realised volatility:

$$CV(t) = I(Z(t) \leq \Phi_\alpha)RV(t) + I(Z(t) > \Phi_\alpha)BV(t). \quad (11)$$

Clearly, the significant jump detection test requires a choice of α . Following prior studies, such as Andersen *et al.* (2010), Andersen *et al.* (2011) and Chan *et al.* (2014), we use a critical value of $\alpha = 0.99$.

It has previously been observed that the financial contagion follows a similar pattern to that of COVID-19 (Akhtaruzzaman *et al.*, 2020; He *et al.*, 2020; Okorie and Lin, 2020). In addition, US markets were one of the main sources of a spillover effect to other markets (Syriopoulos *et al.*, 2015). To assess this pattern, we construct a co-jump variable by summing the number of occurrences when both the stock index and S&P500 display significant jumps on a particular day.

Countries with greater economic development might be thought to be less susceptible to a pandemic (Ding *et al.*, 2020). Similarly, countries with a lower octogenarian population might also be less susceptible. To capture these potential effects, we include GDP and percentage of population aged above 65 (*Population*). The GDP and population data are from The World Bank for the year 2018. The GDP data are in current US dollars and are converted from domestic currencies using single year official exchange rates.

Country risk could be an important factor to explain the variation in stock markets across countries (Greer *et al.*, 2020; Greppmair *et al.*, 2020). We use country risk indices (composite risk rating index, political risk rating index, economic risk rating index, financial risk rating index, and unemployment risk

rating) from Political Risk Services' International Country Risk Guide (ICRG) by the PRS Group.

According to ICRG, the composition risk index comprises 22 variables, representing three major components of country risk, namely economic, financial and political. There are five variables representing each of the economic and financial components of risk, whereas the political component is based on 12 variables. The economic risk rating measures a country's current economic strengths and weaknesses and reflects a country's ability to finance its official, commercial and trade debt obligations. Similarly, the financial risk rating reflects the ability and willingness of a country to service its trade and foreign debt obligations. Finally, the political risk rating measures the political stability of a country, which affects the country's ability to service its financial obligations. The political and the composite (financial and economic) risk indices are each based on 100 (50) points, and range from 0 to 100 (50). In all cases, the lower (higher) the risk points, the higher (lower) the associated risk. Thus, to allow a more intuitive interpretation, we define countries as having high risk factors if their risk rating points are within the first quartile of high-risk factors, and construct *Politic*, *Fin*, *Econ* and *Com* dummy variables, representing political risk, financial risk, economic risk and the composition risk index, respectively. Each variable takes the value of 1 for countries with high-risk factors and 0 otherwise.

Table 1 provides summary statistics regarding the cumulative number of COVID-19 confirmed cases/death, daily growth rates and country risk indices in Panel A, and market quality in Panel B. Several countries have relatively high composite risk ratings (low risk), such as the United States, Italy and Spain. However, the United States has the highest number of confirmed cases and death. Italy and Spain, on the other hand, have the highest growth rates of confirmed cases and deaths, respectively. Yet, the market quality measures are all positive for the United States, while the market quality measures of several countries have mixed responses to the COVID-19 pandemic information. It is therefore interesting to formally test the relation between market quality and severity of COVID-19 given each country's risks such as economic, finance and political risks in the next section.

3.2. Methodology

To examine the impact of changes in COVID-19 confirmed cases/deaths on market quality, we use high-frequency data on daily stock indices to obtain a measurement of market quality. The following baseline model is used:

$$Y(t) = \beta_0 + \beta_1 \text{COVID}(t) + \beta_2' \text{Control}(t) + \varepsilon(t) \quad (12)$$

where the dependent variable, Y , is market quality and proxied by the return, realised volatility, jumps and co-jumps. Our key independent variables is

Table 1
Summary statistics

Panel A									
Country	<i>N</i>	Confirmed cases	Confirmed deaths	Growth in cases	Growth in deaths	Comp risk rating	Econ risk rating	Fin risk rating	Pol risk rating
Argentina	159	538.46	24.98	7.19	4.16	73.5	38.0	41.0	68.0
Australia	135	1115.24	9.64	6.85	3.97	76.5	36.5	34.0	82.5
Austria	132	2403.95	64.17	8.34	6.13	80.5	38.5	38.0	84.5
Bangladesh	101	1.18	0.12	2.99	0.83	61.7	34.5	40.0	49.0
Belgium	134	4845.20	676.35	10.56	7.35	77.7	39.0	37.0	79.5
Canada	166	7433.13	387.19	7.72	6.66	82.7	38.5	39.0	88.0
Chile	162	2278.44	26.94	7.89	4.01	78.0	42.5	39.5	74.0
China	130	26150.24	1116.72	10.83	10.97	74.0	39.5	47.5	61.0
Colombia	160	833.31	32.56	7.73	4.53	68.2	36.5	39.5	60.5
France	134	15949.55	2247.69	11.25	9.13	72.5	36.5	36.5	72.0
Germany	132	19870.86	635.17	11.89	8.11	81.7	41.0	42.5	80.0
Hong Kong	132	0.00	0.00	0.00	0.00	83.2	44.5	42.0	80.0
Hungary	122	135.23	11.57	6.53	5.96	71.0	38.0	30.5	73.5
India	132	3036.38	99.76	11.54	6.73	67.2	34.0	42.0	58.5
Indonesia	133	975.73	80.39	8.74	9.22	68.0	37.5	39.5	59.0
Ireland	158	1722.34	78.58	8.67	5.24	73.2	35.0	33.5	78.0
Israel	132	1577.30	13.94	11.09	3.76	73.7	40.5	41.0	66.0
Italy	132	27453.27	3548.68	20.93	7.97	72.0	35.5	36.0	72.5
Japan	128	1250.46	40.48	8.35	5.93	80.5	36.5	43.5	81.0
Malaysia	135	861.32	14.18	6.67	4.13	77.2	39.5	43.0	72.0
Mexico	161	1698.01	144.91	6.86	5.15	73.0	38.0	40.0	68.0
Netherland	158	4055.80	453.53	8.80	6.87	82.0	40.0	39.0	85.0
Norway	131	1027.64	19.66	9.23	4.99	89.2	45.0	46.0	87.5
Pakistan	133	1753.35	34.84	13.50	4.71	57.0	30.0	39.0	45.0
Philippines	128	1039.31	58.23	10.66	8.51	71.2	37.5	43.0	62.0
Poland	129	1345.58	59.13	10.86	5.80	72.0	35.0	30.5	78.5
Portugal	134	2651.31	93.63	8.53	6.37	69.0	30.0	34.0	74.0
Qatar	135	1480.84	1.59	15.02	2.25	80.2	48.5	41.0	71.0
Romania	130	1234.15	65.65	8.89	5.93	66.2	31.0	34.0	67.5
Russia	131	9446.82	83.26	14.70	6.06	73.2	39.5	45.5	61.5
Saudi Arabia	140	2403.81	19.45	9.75	4.71	81.0	47.0	48.0	67.0
South Korea	162	2890.98	50.06	7.51	3.98	78.5	41.5	41.0	74.5
Spain	134	30019.16	2885.89	12.59	13.49	67.7	33.0	34.0	68.5
Sweden	131	2149.34	247.15	11.20	7.71	85.5	44.0	40.0	87.0
Switzerland	131	3900.31	145.36	12.84	6.46	88.5	43.5	46.5	87.0
Taiwan	129	69.02	1.17	5.96	2.54	84.2	43.0	46.0	79.5
Thailand	132	396.90	5.73	7.23	2.15	70.0	37.5	43.5	59.0
Turkey	137	11519.80	288.41	14.74	8.30	62.0	36.0	30.5	57.5
UK	134	16101.90	2345.19	10.09	10.96	73.7	33.5	38.0	76.0
USA	208	232430.25	12719.44	8.19	7.23	75.5	35.0	33.0	83.0

(continued)

Table 1 (continued)

Panel A									
Country	<i>N</i>	Confirmed cases	Confirmed deaths	Growth in cases	Growth in deaths	<i>Comp</i> risk rating	<i>Econ</i> risk rating	<i>Fin</i> risk rating	<i>Pol</i> risk rating
Ukraine	129	865.08	23.98	9.43	4.35	65.0	33.0	32.0	65.0
UAE	136	1412.28	11.88	9.28	3.86	82.5	46.5	40.5	78.0
Venezuela	149	41.79	0.97	4.88	1.94	62.2	33.5	44.0	47.0
Panel B									
Country	<i>N</i>	Return	RV	Jump	Co-jump				
Argentina	159	0.002290	0.000534	0.000139	0.1635				
Australia	135	−0.001405	0.000269	−0.000015	0.1630				
Austria	132	−0.005882	0.000267	−0.000051	0.1591				
Bangladesh	101	−0.003849	0.000105	−0.000018	0.0693				
Belgium	134	−0.002971	0.000228	−0.000034	0.1791				
Canada	166	0.000850	0.000317	0.000143	0.2831				
Chile	162	−0.001605	0.000186	0.000032	0.1667				
China	130	0.001607	0.000096	−0.000014	0.1077				
Colombia	160	−0.001546	0.000164	0.000001	0.1063				
France	134	−0.001941	0.000259	−0.000017	0.1418				
Germany	132	−0.001475	0.000262	−0.000035	0.1515				
Hong Kong	132	0.000280	0.000103	0.000014	0.1439				
Hungary	122	−0.001998	0.000347	−0.000027	0.0738				
India	132	−0.000590	0.000257	−0.000012	0.1212				
Indonesia	133	−0.001315	0.000119	−0.000025	0.1729				
Ireland	158	−0.001825	0.000295	0.000021	0.1772				
Israel	132	−0.000223	0.000118	−0.000015	0.0682				
Italy	132	−0.003562	0.000327	−0.000017	0.1061				
Japan	128	0.000008	0.000163	−0.000029	0.1563				
Malaysia	135	0.001125	0.000053	−0.000004	0.1630				
Mexico	161	−0.001439	0.000211	0.000096	0.1118				
Netherland	158	−0.000303	0.000351	0.000083	0.2025				
Norway	131	−0.000492	0.000197	−0.000086	0.0916				
Pakistan	133	−0.000081	0.000305	0.000126	0.1504				
Philippines	128	0.000475	0.000283	0.000080	0.1172				
Poland	129	−0.003010	0.000264	−0.000031	0.1085				
Portugal	134	−0.002038	0.000164	−0.000015	0.1493				
Qatar	135	0.000393	0.000065	−0.000012	0.0889				
Romania	130	−0.001728	0.000088	−0.000027	0.1154				
Russia	131	−0.000295	0.000223	−0.000039	0.1069				
Saudi Arabia	140	−0.000349	0.000064	−0.000025	0.1286				
South Korea	162	−0.000144	0.000157	−0.000020	0.0864				
Spain	134	−0.003387	0.000256	−0.000025	0.1493				
Sweden	131	−0.000895	0.000209	−0.000040	0.1374				
Switzerland	131	−0.001141	0.000351	0.000124	0.1145				
Taiwan	129	−0.000080	0.000055	−0.000022	0.1240				
Thailand	132	−0.000712	0.000203	−0.000017	0.1364				

(continued)

Table 1 (continued)

Panel B					
Country	N	Return	RV	Jump	Co-jump
Turkey	137	−0.001297	0.000184	−0.000058	0.0949
UK	134	−0.001880	0.000269	0.000011	0.0970
USA	208	0.001701	0.000433	0.000154	n/a
Ukraine	129	−0.000538	0.000020	0.000001	0.0000
UAE	136	0.000784	0.000160	0.000002	0.0956
Venezuela	149	0.012290	0.000968	0.000538	0.3624

Panel A reports the number and the growth of confirmed cases, deaths, and risk ratings (Composte, Economic, Finance and Political risk ratings) for each country. The average daily return, realised volatility, jumps and co-jumps with S&P500 are reported in Panel B. Our sample encompasses 30 October 2019 to 13 May 2020.

COVID, which is either (i) daily growth in total confirmed cases, (ii) daily growth in total cases of deaths or (iii) both daily growth in total confirmed cases and deaths caused by COVID-19. *Control* comprises control variables, such as GDP, population, unemployment, one period lag growth rate in the cumulative number of confirmed COVID-19 cases/deaths, one period lag stock return, and one period lag realised volatility.

Next, to understand how the country risk and its components (i.e., economic, political and financial) influence the relation between COVID-19 and market quality, we repeat our analyses with additional variables capturing different aspects of country risk. These include *Econ*, *Politic*, *Fin* and *Com*, representing economic risk, political risk, financial risk and the composition risk index, respectively. We define *Econ* as a dummy variable that is equal to one if the country has high economic risk, and zero otherwise; *Politic* as a dummy variable that is equal to one if the country has high political risk, and zero otherwise; *Fin* as a dummy variable that is equal to one if the country has high financial risk, and zero otherwise; and *Com* as a dummy variable that is equal to one if the country has high composite risk, and zero otherwise. Finally, we also include the interaction terms between these risks and the growth in the number of confirmed cases and deaths. To explore the impact of the country risk on the relationship between COVID-19 and the stock market, we run the following regression:

$$Y(t) = \beta_0 + \beta_1 COVID(t) + \beta_2' Control(t) + \beta_3 RISK(t) + \beta_4 COVID(t) RISK(t) + \varepsilon(t) \quad (13)$$

where the dependent variable, *Y*, is market quality and proxied by the return, realised volatility, jumps and co-jumps. *COVID* is as defined for Equation (12). The key explanatory variables are *RISK* and its interactions with *COVID*.

RISK represents either *Econ*, *Politic*, *Fin* or *Com*. *Control* comprises the same variables as for Equation (12).

4. Empirical results

Table 2 reports the baseline regression results of panel data for 43 stock indices around the world. The results suggest that COVID-19 (i.e., the growth in the number of confirmed cases) has a positive and a significant impact on financial volatility, jumps and co-jumps, but a negative impact on financial returns. This finding is in line with previous studies that also identify the adverse effect of COVID-19 on stock market quality (Alan *et al.*, 2020; Ashraf, 2020; Baker *et al.*, 2020; Ramelli and Wagner, 2020). This finding implies that, during the COVID-19 pandemic, market participants incorporate news about the pandemic into their valuation. Another possible explanation for this finding is that the COVID-19 pandemic changed the way market participants perceive risk, which results in an increased volatility of markets due to more homogeneous beliefs of market participants who expect higher levels of risk (Burns *et al.*, 2012). Furthermore, the coefficient of COVID in the co-jumps model is positive and significant, suggesting a possible spillover effect of the pandemic. When the number of confirmed cases increases, stock market indices around the world appear to jump with the US stock market. These results are consistent with findings of spillover effects between Asian countries and European and American countries (Akhtaruzzaman *et al.*, 2020; He *et al.*, 2020; Okorie and Lin, 2020). In contrast, the growth rate of cumulative deaths only has a positive impact on the realised volatility model. This result may be explained by the fact that the market participants are already pricing the effect of the pandemic by using new confirmed cases (Ashraf, 2020). To ensure that our results are not driven by multicollinearity between the daily growth rate in confirmed cases and the daily growth rate in deaths, we also run two separate regressions with each of these two variables representing COVID-19 infection.⁹ The results of growth in death/cases remain similar. Furthermore, our regressions include one period lag in the growth rate of the cumulative number of confirmed COVID-19 cases/deaths, which capture the impact of past confirmed cases/death growth rate on the current stock market performance. Thus, our results remain similar and are unlikely driven by historical growth rate of COVID-19 cases/deaths.

Table 3 reports the effect of economic risk on the relation between the growth in COVID-19 confirmed cases/deaths and market quality. Consistent with the baseline model, COVID-19 has a significant impact on market quality. Surprisingly, in all the models, we fail to highlight the impact of economic risk

⁹We run separate regressions for the daily growth rate in confirmed cases and the daily growth rate in deaths in all analyses. The results remain consistent. To save space, these results are not reported and are available upon request.

Table 2

Baseline panel regression of the relation between COVID-19 cases/deaths data and market quality

	Return	RV	Jump	Co-jump
<i>COVID</i>	−0.288*** (0.0958)	0.0788*** (0.0288)	0.00219** (0.00109)	0.00151** (0.000753)
<i>Lagged COVID</i>	−0.109 (0.0830)	0.0947** (0.0371)	0.00135 (0.000846)	0.000871 (0.000611)
<i>GDP</i>	−2.241 (5.617)	1.290 (1.582)	0.121 (0.0862)	0.0441 (0.119)
<i>Population</i>	−1.253 (1.314)	0.481 (0.392)	0.0222 (0.0227)	0.00749 (0.0305)
<i>Unemployment</i>	2.301 (13.61)	3.496 (2.676)	0.582*** (0.221)	0.0691 (0.301)
<i>Death</i>	0.0432 (0.186)	0.172*** (0.0624)	0.00137 (0.00113)	−0.000246 (0.00117)
<i>Lagged_Death</i>	0.0224 (0.161)	0.435 (0.273)	0.00181 (0.00115)	0.00105 (0.00112)
<i>Lagged return</i>	0.0890*** (0.0293)			
<i>Lagged RV</i>		0.378*** (0.0703)		
Constant	6.263 (54.42)	−10.75 (11.61)	−3,320*** (0.931)	−2.617** (1.238)
Country fixed effects	Yes	Yes	Yes	Yes
Observations	5,460	5,460	5,534	5,295
R^2	0.040	0.302		

This table reports results from our baseline panel regression, where dependent variables are daily return (Return), daily realised volatility (RV), and jumps and co-jumps with S&P500. Our key variables of interest are the growth rate of cumulative confirmed cases (*COVID*) and the growth rate of cumulative death cases (*Death*). We also control for the percentage of the population aged above 65, GDP and unemployment risk. For return and realised volatility, we also control for lagged return and lagged RV. Our sample encompasses 30 October 2019 to 13 May 2020. The robust standard errors are reported in parentheses. ***, **, * indicates significance at the 1, 5 and 10 percent levels, respectively.

on market quality when there is an exogenous economic shock from the pandemic. This finding is contrary to previous studies that examine the impact of the pandemic at the firm level, which suggests that stock markets in richer economies suffer less during the crisis (Ding *et al.*, 2020). This inconsistent finding could be due to different samples, periods of study, level of analysis and control variables. Unlike previous studies, we run the analysis at the aggregate country level. In addition, we also control for the unemployment factor, which appears to significantly influence the country-level financial immunity to the pandemic (Zaremba *et al.*, 2021b). Though the economic risk may influence the country's ability to pay back its debts, it indirectly affects the performance of

Table 3
Effect of economic risk on the relation between COVID-19 cases/deaths data and market quality

	Return	Return	RV	RV	Jump	Jump	Cojump	Cojump
<i>COVID</i>	−0.288*** (0.0958)	−0.280*** (0.101)	0.0788*** (0.0288)	0.0817*** (0.0312)	0.00219** (0.00109)	0.00254* (0.00130)	0.00151** (0.000753)	0.00156* (0.000817)
<i>Lagged_COVID</i>	−0.109 (0.0830)	−0.109 (0.0832)	0.0947** (0.0371)	0.0945** (0.0371)	0.00135 (0.000846)	0.00130 (0.000851)	0.000871 (0.000611)	0.000866 (0.000613)
<i>GDP</i>	−2.241 (5.617)	−2.277 (5.619)	1.290 (1.582)	1.308 (1.583)	0.121 (0.0862)	0.121 (0.0862)	0.0441 (0.119)	0.0436 (0.119)
<i>Population</i>	−1.253 (1.314)	−1.248 (1.314)	0.481 (0.392)	0.481 (0.393)	0.0222 (0.0227)	0.0224 (0.0227)	0.00749 (0.0305)	0.00757 (0.0305)
<i>Unemployment</i>	2.301 (13.61)	2.274 (13.62)	3.496 (2.676)	3.534 (2.689)	0.582*** (0.221)	0.584*** (0.222)	0.0691 (0.301)	0.0685 (0.301)
<i>Econ</i>	6.131 (15.64)	3.848 (15.48)	−5.170 (5.016)	−3.384 (5.145)	0.282 (0.281)	0.307 (0.283)	0.450 (0.370)	0.415 (0.372)
<i>Death</i>	0.0432 (0.186)	0.0253 (0.191)	0.172*** (0.0624)	0.180*** (0.0629)	0.00137 (0.00113)	0.00130 (0.00115)	−0.000246 (0.00117)	−0.000504 (0.00123)
<i>Lagged_Death</i>	0.0224 (0.161)	0.0180 (0.161)	0.435 (0.273)	0.437 (0.274)	0.00181 (0.00115)	0.00180 (0.00115)	0.00105 (0.00112)	0.00101 (0.00113)
<i>Covid × Econ</i>		−0.0974 (0.182)		−0.0363 (0.0645)		−0.00338 (0.00214)		−0.000557 (0.00196)
<i>Death × Econ</i>		0.474 (0.507)		−0.223 (0.146)		0.000851 (0.00529)		0.00526 (0.00581)

(continued)

Table 3 (continued)

	Return	Return	RV	RV	Jump	Jump	Cojump	Cojump
<i>Lagged return</i>	0.0890*** (0.0293)	0.0886*** (0.0293)						
<i>Lagged RV</i>			0.378*** (0.0703)	0.378*** (0.0704)				
Constant	6.263 (54.42)	6.453 (54.46)	-10.75 (11.61)	-11.00 (11.67)	-3.320*** (0.931)	-3.332*** (0.933)	-2.617** (1.238)	-2.613** (1.238)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,460	5,460	5,460	5,460	5,534	5,534	5,295	5,295
R^2	0.040	0.040	0.302	0.302				

This table reports results from our panel regression, where dependent variables are daily return (Return), daily realised volatility (RV), and jumps and co-jumps with S&P500. Our key variables of interest are the growth rate of cumulative confirmed cases (*COVID*) and the growth rate of cumulative death cases (*Death*). We also control for the percentage of the population aged above 65, GDP and unemployment risk. For return and realised volatility, we also control for lagged return and lagged RV. Our sample encompasses 30 October 2019 to 13 May 2020. The robust standard errors are reported in parentheses. ***, **, * indicates significance at the 1, 5 and 10 percent levels, respectively. *Econ* is a dummy variable equal to one for a country with a high economic risk rating, zero otherwise.

the stock market. For this reason, this information may not be priced in by stock market investors.

Previous studies suggest that country-level political characteristics can play a role in explaining the stock market reaction to COVID-19 (Bosancianu *et al.*, 2020; Ding *et al.*, 2020; Erdem, 2020; Greer *et al.*, 2020). In line with these studies, we repeat our analyses considering political risk (Table 4); the coefficients for COVID-19 confirmed cases remain significant in all models, while confirmed death is only significant in the realised volatility models. This result is consistent with our main finding. Our focus, however, is on the interaction term between COVID and political risk. This interaction term shows the marginal effect of COVID on market quality when a country has high political risk. The regression analysis in Table 4 shows the interaction term for the jump model is negative and statistically significant.¹⁰ This suggests that countries with low political stability experienced lower volatility in stock indices as the number of COVID-19 cases grew. A possible explanation for this might be that during the pandemic, people turned to the state for leadership and unified action, and thus countries with centralised power are likely to have taken forceful or appropriate action to prevent the spread of the virus, resulting in less panic in the stock market. This finding is supported by Ding *et al.* (2020), who find that countries with civil and socialist legal traditions experienced less decline in stock prices than those with a common law tradition. Along similar lines, Zaremba *et al.* (2021b) points out that countries with less freedom of expression were better able to cope with the adverse consequences of the pandemic.

Table 5 focuses on the impact of fiscal capacity on stock market returns during the COVID-19 crisis. We find that the coefficients for the interaction terms between COVID and financial risk are insignificant in the full models. However, when we examine only the confirmed COVID-19 cases, the interaction term is negative and significant in the return model.⁹ This implies that countries with high financial risk were able to ameliorate the adverse effects of COVID-19 on market returns. These results are consistent with other studies (Gerding *et al.*, 2020; Greppmair *et al.*, 2020). This result may be explained by the fact that countries with greater financial flexibility are more able to fund an appropriate stimulus package, which is used to offset the effects of the pandemic.

To evaluate how country risk shapes stock price movements in response to the COVID-19 pandemic, we retest our baseline model by using composite risk as a proxy for country risk (Table 6). The composite risk is a simple function of the economic, political and financial risk indices. Consistent with our baseline model, the coefficient of *COVID* is negative and significant for market return

¹⁰When we examine the COVID-19 confirmed cases only, the interaction terms in the RV and jump models are also negative and statistically significant. To save space, the results are not reported here, but are available upon request.

Table 4
Effect of political risk on the relation between COVID-19 cases/deaths data and market quality

	Return	Return	RV	RV	Jump	Jump	Cojump	Cojump
<i>COVID</i>	−0.288*** (0.0958)	−0.288*** (0.104)	0.0788*** (0.0288)	0.0870*** (0.0331)	0.00219** (0.00109)	0.00260* (0.00133)	0.00151** (0.000753)	0.00169** (0.000852)
<i>Lagged_COVID</i>	−0.109 (0.0830)	−0.109 (0.0832)	0.0947** (0.0371)	0.0932** (0.0370)	0.00135 (0.000846)	0.00127 (0.000847)	0.000871 (0.000611)	0.000841 (0.000613)
<i>GDP</i>	−2.241 (5.617)	−2.293 (5.619)	1.290 (1.582)	1.293 (1.580)	0.121 (0.0862)	0.121 (0.0862)	0.0441 (0.119)	0.0443 (0.119)
<i>Population</i>	−1.253 (1.314)	−1.254 (1.314)	0.481 (0.392)	0.483 (0.393)	0.0222 (0.0227)	0.0224 (0.0227)	0.00749 (0.0305)	0.00763 (0.0306)
<i>Unemployment</i>	2.301 (13.61)	2.246 (13.61)	3.496 (2.676)	3.524 (2.683)	0.582*** (0.221)	0.585*** (0.222)	0.0691 (0.301)	0.0709 (0.301)
<i>Politic</i>	9.194 (25.35)	1.214 (25.32)	6.902 (7.443)	8.987 (7.323)	0.356 (0.345)	0.450 (0.348)	0.413 (0.471)	0.470 (0.471)
<i>Death</i>	0.0432 (0.186)	0.0164 (0.187)	0.172*** (0.0624)	0.173*** (0.0626)	0.00137 (0.00113)	0.00141 (0.00116)	−0.000246 (0.00117)	−0.000167 (0.00116)
<i>Lagged_Death</i>	0.0224 (0.161)	0.0241 (0.162)	0.435 (0.273)	0.434 (0.273)	0.00181 (0.00115)	0.00180 (0.00115)	0.00105 (0.00112)	0.00104 (0.00112)
<i>Covid × Politic</i>		0.00516 (0.170)		−0.0948 (0.0631)		−0.00398** (0.00198)		−0.00219 (0.00212)
<i>Death × Politic</i>		1.689 (1.401)		−0.171 (0.423)		−0.00832 (0.00808)		−0.00483 (0.00766)

(continued)

Table 4 (continued)

	Return	Return	RV	RV	Jump	Jump	Cojump	Cojump
<i>Lagged return</i>	0.0890*** (0.0293)	0.0859*** (0.0293)						
<i>Lagged RV</i>			0.378*** (0.0703)	0.378*** (0.0706)				
Constant	6.263 (54.42)	6.695 (54.41)	–10.75 (11.61)	–10.95 (11.63)	–3.320*** (0.931)	–3.336*** (0.933)	–2.617** (1.238)	–2.627** (1.240)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,460	5,460	5,460	5,460	5,534	5,534	5,295	5,295
R^2	0.040	0.041	0.302	0.302				

This table reports results from our panel regression, where dependent variables are daily return (Return), daily realised volatility (RV), and jumps and co-jumps with S&P500. Our key variables of interest are the growth rate of cumulative confirmed cases (*COVID*) and the growth rate of cumulative death cases (*Death*). We also control for the percentage of the population aged above 65, GDP and unemployment risk. For return and realised volatility, we also control for lagged return and lagged RV. Our sample encompasses 30 October 2019 to 13 May 2020. The robust standard errors are reported in parentheses. ***, **, * indicates significance at the 1, 5 and 10 percent levels, respectively. *Politic* is a dummy variable equal to one for a country with a high political risk rating, zero otherwise.

Table 5
Effect of financial risk on the relation between COVID-19 cases/deaths data and market quality

	Return	Return	RV	RV	Jump	Jump	Cojump	Cojump
<i>COVID</i>	-0.288*** (0.0958)	-0.258*** (0.0985)	0.0788*** (0.0288)	0.060*** (0.0256)	0.00219*** (0.00109)	0.00174* (0.00101)	0.00151*** (0.000753)	0.00136* (0.000796)
<i>Lagged_COVID</i>	-0.109 (0.0830)	-0.101 (0.0819)	0.0947*** (0.0371)	0.0911*** (0.0356)	0.00135 (0.000846)	0.00126 (0.000806)	0.000871 (0.000611)	0.000836 (0.000604)
<i>GDP</i>	1.286 (5.518)	1.248 (5.537)	-0.0150 (1.718)	0.0889 (1.721)	0.0525 (0.0996)	0.0558 (0.100)	-0.0705 (0.144)	-0.0682 (0.145)
<i>Population</i>	-2.152 (1.589)	-2.292 (1.597)	0.813* (0.455)	0.821* (0.454)	0.0396 (0.0280)	0.0400 (0.0282)	0.0367 (0.0400)	0.0378 (0.0402)
<i>Unemployment</i>	-9.004 (18.50)	-10.02 (18.55)	7.678** (3.373)	7.827** (3.357)	0.802*** (0.305)	0.807*** (0.307)	0.436 (0.452)	0.447 (0.454)
<i>Fin</i>	-19.85 (18.76)	-15.20 (18.72)	7.341*** (3.540)	6.183* (3.500)	0.386 (0.371)	0.349 (0.372)	0.645 (0.574)	0.613 (0.576)
<i>Death</i>	0.0432 (0.186)	0.159 (0.229)	0.172*** (0.0624)	0.199*** (0.0753)	0.00137 (0.00113)	0.00172 (0.00145)	-0.000246 (0.00117)	-0.000701 (0.00154)
<i>Lagged_Death</i>	0.0224 (0.161)	0.0218 (0.161)	0.435 (0.273)	0.432 (0.273)	0.00181 (0.00115)	0.00176 (0.00115)	0.00105 (0.00112)	0.00106 (0.00113)
<i>Covid × Fin</i>		-0.246 (0.157)	0.134 (0.0912)	0.134 (0.0912)		0.00298 (0.00190)		0.00125 (0.00190)
<i>Death × Fin</i>		-0.322 (0.299)	-0.0830 (0.0824)	-0.0830 (0.0824)		-0.00115 (0.00223)		0.00130 (0.00241)

(continued)

Table 5 (continued)

	Return	Return	RV	RV	Jump	Jump	Cojump	Cojump
<i>Lagged return</i>	0.0890*** (0.0293)	0.0877*** (0.0293)						
<i>Lagged RV</i>			0.378*** (0.0703)	0.376*** (0.0701)				
Constant	46.46 (70.19)	49.97 (70.40)	–25.62* (13.42)	–26.26** (13.33)	–4.101*** (1.189)	–4.123*** (1.198)	–3.923** (1.713)	–3.966** (1.725)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,460	5,460	5,460	5,460	5,534	5,534	5,295	5,295
R^2	0.040	0.041	0.302	0.303				

This table reports results from our panel regression, where dependent variables are daily return (Return), daily realised volatility (RV), and jumps and co-jumps with S&P500. Our key variables of interest are the growth rate of cumulative confirmed cases (*COVID*) and the growth rate of cumulative death cases (*Death*). We also control for the percentage of the population aged above 65, GDP and unemployment risk. For return and realised volatility, we also control for lagged return and lagged RV. Our sample encompasses 30 October 2019 to 13 May 2020. The robust standard errors are reported in parentheses. ***, **, * indicates significance at the 1, 5 and 10 percent levels, respectively. *Fin* is a dummy variable equal to one for a country with a high financial risk rating, zero otherwise.

Table 6
Effect of composite risk on the relation between COVID-19 cases/deaths data and market quality

	Return	Return	RV	RV	Jump	Jump	Cojump	Cojump
<i>COVID</i>	−0.288*** (0.0958)	−0.270*** (0.104)	0.0788*** (0.0288)	0.0916*** (0.0362)	0.00219*** (0.00109)	0.00247* (0.00138)	0.00151*** (0.000753)	0.00184* (0.000955)
<i>Lagged_COVID</i>	−0.109 (0.0830)	−0.110 (0.0830)	0.0947*** (0.0371)	0.0948*** (0.0375)	0.00135 (0.000846)	0.00133 (0.000854)	0.000871 (0.000611)	0.000866 (0.000620)
<i>GDP</i>	−10.00 (10.59)	−10.01 (10.60)	4.160*** (2.073)	4.167*** (2.067)	0.272 (0.180)	0.272 (0.180)	0.296 (0.270)	0.296 (0.271)
<i>Population</i>	−5.844 (4.577)	−5.799 (4.582)	2.179** (0.981)	2.164** (0.982)	0.111 (0.0884)	0.112 (0.0885)	0.157 (0.136)	0.157 (0.136)
<i>Unemployment</i>	−48.61 (51.91)	−48.27 (51.96)	22.33*** (9.503)	22.24*** (9.512)	1.571 (0.976)	1.575 (0.977)	1.723 (1.512)	1.726 (1.513)
<i>Com</i>	−59.33 (56.07)	−62.59 (56.21)	21.94*** (10.58)	25.56*** (10.51)	1.153 (1.108)	1.185 (1.111)	1.927 (1.715)	2.004 (1.717)
<i>Death</i>	0.0432 (0.186)	0.00775 (0.193)	0.172*** (0.0624)	0.186*** (0.0630)	0.00137 (0.00113)	0.00132 (0.00117)	−0.000246 (0.00117)	−0.000165 (0.00118)
<i>Lagged_Death</i>	0.0224 (0.161)	0.0138 (0.161)	0.435 (0.273)	0.439 (0.274)	0.00181 (0.00115)	0.00181 (0.00115)	0.00105 (0.00112)	0.00106 (0.00113)
<i>Covid × Com</i>		−0.118 (0.158)		−0.0860* (0.0481)		−0.00149 (0.00234)		−0.00299 (0.00200)
<i>Death × Com</i>		0.653 (0.631)		−0.307* (0.160)		2.69e−05 (0.00483)		−0.00293 (0.00511)

(continued)

Table 6 (continued)

	Return	Return	RV	RV	Jump	Jump	Cojump	Cojump
<i>Lagged return</i>	0.0890*** (0.0293)	0.0878*** (0.0292)						
<i>Lagged RV</i>			0.378*** (0.0703)	0.377*** (0.0704)				
Constant	228.1 (223.1)	226.7 (223.4)	−92.80** (40.84)	−92.63** (40.86)	−7.630* (4.237)	−7.647* (4.242)	−9.823 (6.554)	−9.840 (6.559)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,460	5,460	5,460	5,460	5,534	5,534	5,295	5,295
R^2	0.040	0.040	0.302	0.303				

This table reports results from our panel regression, where dependent variables are daily return (Return), daily realised volatility (RV), and jumps and co-jumps with S&P500. Our key variables of interest are the growth rate of cumulative confirmed cases (*COVID*) and the growth rate of cumulative death cases (*Death*). We also control for the percentage of the population aged above 65, GDP and unemployment risk. For return and realised volatility, we also control for lagged return and lagged RV. Our sample encompasses 30 October 2019 to 13 May 2020. The robust standard errors are reported in parentheses. ***, **, * indicates significance at the 1, 5 and 10 percent levels, respectively. *Com* is a dummy variable equal to one for a country with a high composite risk rating, zero otherwise.

and positively related to realised volatility, jumps and co-jumps of the stock indices. The interaction terms between the COVID-19 confirmed cases, deaths, and the composite risk index are negative and significant for the realised volatility models.¹¹ This may suggest that countries with low stability overall experience lower volatility in their stock indices. Although this result is rather surprising, one explanation is that in countries with low stability, people often must rely on themselves and react to the pandemic sooner, thus resulting in a lower volatility in the markets. This is also consistent with Abuzayed *et al.* (2021) who find that developed markets transmitted and received more marginal extreme risk during the COVID-19 pandemic. Unfortunately, for other measures of market quality, this study finds a weak association with country risk. Thus, it is not clear whether stock markets in richer economies, more indebted countries or with more state power have reacted differently to COVID-19. A possible explanation for this result is that economic and political risks can be intertwined. For instance, a country with strong economic health may not be a good candidate for investment if the political climate is unwelcoming to outside investors.

5. Conclusion

We have examined the impact of COVID-19 on financial markets around the world by utilising intraday data and the Barndorff-Nielsen and Shephard (2004) nonparametric jump detection technique. To this end, we have used stock return, realised volatility, jumps and co-jumps as a proxy for market quality and we have explored whether country risk plays a significant role in the relation between COVID-19 and market quality. The outcomes of our empirical investigation underline the fact that: (i) the growth in cumulative COVID-19 confirmed cases amplifies realised volatility and jumps while reducing returns; (ii) the impact of COVID-19 on volatility is weaker in high political risk countries; and (iii) the impact of COVID-19 on market return is stronger in high financial risk countries. Our findings have important implications for financial market participants. This study provides insights about the stock market response to the pandemic and how country characteristics play an important role in shaping the stock market response to COVID-19-induced financial market instability. Future research could potentially evaluate different jump detection techniques for extremely volatile periods similar to the COVID-19 pandemic.

¹¹For realised volatility, the interaction terms between the COVID-19 confirmed cases, death, and the composite risk in the separate models are also negative and significant. The results are not reported here and are available upon request.

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